TI ONE VOICE PLATFORM

Strategic Data Architecture
& Analysis Blueprint

A Comprehensive Guide to Building
an Evidence-Construction Engine

Written in Plain Language with Technical Explanations

Version 2.0 — February 7th 2026
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Executive Summary: What This Document Is About

This document is a roadmap for turning the TI One Voice platform into something much more powerful than a place for Targeted Individuals to tell their stories. The goal is to build a system that collects information from thousands of TIs, stores it in smart ways, and then uses computers and artificial intelligence to find hidden patterns, connections, and evidence that no single person could ever spot on their own.

Think of it like this: one person reporting a crime is easy to ignore. But when thousands of people independently report the same crime, with overlapping details, similar timelines, and shared perpetrators, that becomes impossible to dismiss. The challenge is organizing all that information so the patterns actually emerge from the noise.

> **THE CORE IDEA IN ONE SENTENCE**
>
> If we collect the right data, in the right format, from enough people, over enough time, the evidence will construct itself — the patterns in the data will point to who is responsible, how they operate, and where the proof can be found.

This blueprint covers seven major areas: (1) whether the current interview questionnaires are asking the right questions in the right way, (2) how to store data so it can be analyzed years from now, (3) what analysis techniques to apply as the dataset grows, (4) how to turn raw data into legally admissible evidence, (5) how TIs should use the platform for maximum impact, (6) a year-by-year implementation plan, and (7) the risks and how to manage them.

The document is deliberately written in plain language. Every technical concept is explained. Where real-world examples or case studies from other fields help illustrate a point, they are included. The aim is for any TI, regardless of technical background, to understand the strategy and their role in it.

Why a Data-Driven Approach Can Work

Before diving into the technical details, it is worth understanding why this approach, collecting and analyzing data from many people, has worked in other situations where powerful actors operated in secrecy and their victims were initially disbelieved.

The Power of Aggregate Data

When one person tells a story, it can be dismissed as anecdotal, delusional, or exaggerated. When a hundred people tell similar stories independently, it becomes a pattern. When a thousand people provide detailed, timestamped, corroborating accounts, it becomes evidence that demands investigation. This principle has been proven in multiple real-world cases.

REAL-WORLD CASE: The Catholic Church Abuse Scandal

For decades, individual victims who reported abuse by Catholic priests were dismissed, discredited, or silenced. The breakthrough came when investigative journalists and lawyers began systematically collecting and cross-referencing reports from hundreds of victims across different parishes, cities, and countries. The pattern that emerged — similar methods, institutional cover-up protocols, transfer of accused priests to new parishes — proved that this was not isolated incidents but a systematic institutional problem. The 2002 Boston Globe investigation (portrayed in the film Spotlight) succeeded precisely because they built a database of cases and looked for patterns across them. No single victim's testimony would have brought down the system. The aggregate data did.

REAL-WORLD CASE: The Flint Water Crisis

Residents of Flint, Michigan complained for months that their tap water looked, smelled, and tasted wrong, and that they and their children were getting sick. Government officials repeatedly told them the water was safe. The breakthrough came when Dr. Mona Hanna-Attisha, a pediatrician, collected blood lead level data from hundreds of children and mapped it geographically. The data showed that children in areas served by Flint River water had lead levels two to three times higher than before the water source was switched. This was not one person's complaint; it was systematic, geographic, statistical evidence that proved both the contamination and the official cover-up. The methodology was simple: collect the same data point from many people, organize it by location and time, and let the pattern speak.

REAL-WORLD CASE: Havana Syndrome

Starting in 2016, US and Canadian diplomats in Havana, Cuba began reporting unusual symptoms: sudden onset of vertigo, headaches, ear pain, nausea, and cognitive difficulties. Initially, individual reports were met with skepticism. However, as the number of affected individuals grew (eventually over 200 across multiple countries including China, Russia, Austria, and the US itself), and as their symptoms were systematically documented and compared, patterns emerged. Many reported hearing a loud piercing sound before symptom onset. Medical examinations revealed brain abnormalities consistent with directed energy exposure. A 2020 National Academy of Sciences report concluded that 'directed, pulsed radio frequency energy' was the most plausible explanation. This case is directly relevant because it demonstrates how systematic documentation of experiences that are initially dismissed can eventually compel official investigation. Critically, it was the consistency of independently reported symptoms across geographically dispersed individuals that transformed individual complaints into a recognized phenomenon.

REAL-WORLD CASE: MKUltra — How Secret Government Programs Were Exposed

From 1953 to 1973, the CIA ran a secret program called MKUltra that conducted experiments on unwitting human subjects, including mind control techniques, drug administration (particularly LSD), sensory deprivation, and psychological torture. The program was classified and denied for over two decades. It was only exposed through a combination of investigative journalism, FOIA (Freedom of Information Act) requests, and the accidental discovery of financial records that the CIA had failed to destroy. In 1977, a FOIA request yielded 20,000 documents that the CIA had misfiled. These documents, when systematically analyzed, revealed the scope, methods, and institutional structure of the program. Senate hearings (the Church Committee) followed. The lesson: even the most powerful secret programs leave traces in data. Financial records, personnel records, procurement records, communication records — the documentary evidence accumulates even when the program operators try to destroy it. The TI One Voice platform is essentially building the equivalent of those 20,000 documents, but from the victim side.

REAL-WORLD CASE: COINTELPRO — FBI's Domestic Surveillance Program

From 1956 to 1971, the FBI's Counter Intelligence Program (COINTELPRO) systematically targeted, surveilled, harassed, and disrupted domestic political organizations and individuals. Tactics included infiltration, psychological warfare, legal harassment, and extralegal violence. Targets included civil rights leaders, anti-war activists, and others. The program was secret until 1971, when activists broke into an FBI field office in Media, Pennsylvania and stole over 1,000 classified documents, which they then distributed to journalists. The stolen documents revealed the systematic nature of the harassment. Subsequent investigations (the Church Committee again) confirmed that the FBI had conducted over 2,000 COINTELPRO operations. The relevance here is twofold: (1) governments have a documented history of conducting secret programs that target individuals and groups, and (2) these programs were exposed through systematic documentation and data — first the stolen documents, then the congressional investigations that cross-referenced testimony from multiple victims and government insiders.

These cases share a common thread: systematic data collection from multiple sources, organized for cross-referencing and pattern detection, is what transforms individual complaints into undeniable evidence. The TI One Voice platform is designed to be exactly this kind of systematic data collection instrument.

Part I: Are the Interview Questionnaires Asking the Right Questions?

1.1 What You Have: Five Interview Types

The platform currently has five different interview questionnaires, each designed to capture a different aspect of a TI's experience. Think of these as five different lenses, each focusing on a different part of the picture. Together, they should create a complete, detailed portrait of what is happening to each TI.

WHAT IS AN 'INTERVIEW TEMPLATE'?

An interview template is a structured questionnaire with specific questions, response options, and guidance notes. Unlike a simple form, these templates include both free-text fields (where TIs can write in their own words) and structured fields (where they choose from predefined options like 'mild/moderate/severe' or checkboxes). The structured fields are what make computer analysis possible. A computer can easily count how many TIs selected 'severe' for sleep disruption, but it cannot easily understand a paragraph of freeform text. Having both types of fields gives you the best of both worlds: human-readable narratives AND machine-analyzable data.

Interview Type	What It Captures	When To Use	Overall Assessment
TI Start (Onset)	The complete story of how targeting began: personal background, circumstances at onset, first symptoms, life situation, consent and legal context	Once, during onboarding	Excellent. The cornerstone of the system.
Attack	Details of specific attacks: type (V2K, DEW, etc.), physical sensations, timing, location, reactions, countermeasures tried, impact on daily life	After each significant attack	Strong. Needs better timestamps for repeat use.
Clues (Evidence)	Investigative leads: persons of interest, organized stalking observations, institutional connections, electronic anomalies, physical evidence, digital surveillance, financial anomalies, reports to authorities	Monthly updates	The most analytically valuable template. Essential for cross-case analysis.
Damages	Losses and harms: employment, financial, family relationships, social isolation, reputation, housing, physical health, mental health, dignity	Quarterly reassessment	Well-designed for legal and advocacy purposes.
Life Event	Significant life events during the targeting period: health changes, relationship changes, financial events, legal events. Tracks whether events correlate with targeting patterns.	Each time a significant event occurs	Innovative. Critical for building the timeline.

1.2 What Is Working Well

- **The mix of structured and free-text fields:** This is crucial. When a TI selects 'directed_energy_weapon_dew' from a checklist AND writes a detailed description of the burning sensation in their own words, the platform gets both: a data point that a computer can count and compare across thousands of TIs, and a human story that conveys the lived experience. Many data collection systems make the mistake of being entirely structured (losing the story) or entirely freeform (making computer analysis nearly impossible). Your templates strike the right balance.
- **The investigative orientation of the Clues interview:** This template is the analytical engine of the system. It asks about persons of interest with their connections, organized stalking with identifying details, electronic anomalies with technical specifics, and digital surveillance with traceable evidence. These are exactly the kinds of data points that, when aggregated across hundreds of TIs, can reveal networks and patterns.
- **Longitudinal design (tracking changes over time):** The Damages interview includes assessment periods and the Life Event interview is designed for repeated submissions. This is extremely important because it lets you track trajectories: is the situation getting better or worse? Did filing a police report lead to an escalation in attacks? Did moving to a new city reduce symptoms? These before-and-after comparisons are powerful analytical tools.

WHAT DOES 'LONGITUDINAL' MEAN?

In research, 'longitudinal' means collecting data from the same people over an extended period of time, rather than just a single snapshot. A snapshot (also called 'cross-sectional') tells you what things look like right now. A longitudinal dataset tells you how things change over time. For example, knowing that '73% of TIs report sleep disruption' is useful. But knowing that '43% of TIs who filed police reports experienced an escalation in sleep disruption within 30 days of filing' is dramatically more useful — it suggests a cause-and-effect relationship. Longitudinal data is what makes this possible.

- **Legal alignment:** Every template references specific articles and sections of the TI One Voice Declaration. This means the data collected maps directly onto legal arguments, which is essential if the evidence is ever presented in court or to a regulatory body.
- **Trauma-informed approach:** The interviewer guidance notes include instructions to pause if a TI becomes distressed, provide support resources, and handle suicidal ideation with appropriate care. This is not just ethically important; it also protects the legal validity of the data, since testimony gathered under duress can be challenged.

1.3 What Needs to Change: Critical Gaps

1.3.1 You Need a Sixth Interview Type: Environmental Baseline

This is the single most important recommendation in this entire document. Currently, all five interview types capture subjective experiences: what the TI felt, saw, heard, and believes. What is missing is a template for capturing objective, measurable, repeatable data about the TI's physical environment.

Why does this matter so much? Because in any legal, scientific, or regulatory context, objective measurements carry far more weight than subjective testimony. A TI saying 'I feel burning in my legs' is important but difficult to prove. A TI showing that the RF (radio frequency) radiation levels inside their apartment are 100 times higher than the readings in their neighbor's apartment is a measurable fact that demands explanation.

WHAT ARE RF/EMF MEASUREMENTS?

RF stands for Radio Frequency — the invisible electromagnetic waves used by cell phones, WiFi routers, TV broadcasts, radar, and many other technologies. EMF stands for Electromagnetic Field — a broader term that includes RF as well as lower-frequency fields from power lines, appliances, etc. Both can be measured with relatively affordable equipment (starting from about €50 for basic detectors, up to €1,000+ for professional spectrum analyzers). The readings are expressed in units like V/m (volts per meter) or mW/cm² (milliwatts per square centimeter). What matters is not the absolute numbers, but whether the numbers are unusual compared to normal background levels and compared to other locations. If a TI's bedroom consistently shows RF levels 10x higher than the street outside, that is anomalous and measurable.

The Environmental Baseline interview should capture:

- **RF/EMF measurements:** What equipment was used (make, model), where in the home/workplace the measurements were taken, at what time of day, and what readings were obtained. The same measurement taken at the same location every week creates a time series that can show spikes correlating with attacks.
- **WiFi and Bluetooth environment:** What networks are visible? What devices appear? Do unusual network names (SSIDs) appear and disappear? This data is machine-readable and verifiable. If an unusual WiFi network named 'surveillance-node-7' appears near three different TIs' homes, that is a concrete investigative lead.
- **Physical environment changes:** New cell towers near the residence, new satellite dishes on neighboring buildings, unusual vehicles with antennas parked nearby, construction activities. Documented with photos and GPS coordinates.
- **Device behavior logs:** Systematic recording of phone and computer anomalies: unexplained battery drain, apps launching by themselves, unusual network traffic, calls or messages to unknown numbers appearing in logs. Screenshots with timestamps.

Why Environmental Data Matters: The Erin Brockovich Analogy

In the famous case of Brockovich v. Pacific Gas & Electric, the breakthrough was not victim testimony alone (though that mattered). It was the systematic collection of water quality data — objective measurements of hexavalent chromium levels in groundwater — that proved contamination. Similarly, if the TI One Voice platform can collect standardized RF/EMF measurements from thousands of TIs, and those measurements show statistically significant anomalies compared to the general population or compared to similar locations without TI residents, that constitutes scientific evidence of environmental anomalies that demands explanation.

1.3.2 Standardize the Measurement Scales

Right now, different interview templates use different scales to measure similar things, and this creates a real problem for analysis. It is like having one thermometer that reads in Celsius and another in Fahrenheit without labeling which is which. Here are the specific issues:

- **Severity scales are inconsistent:** The Attack interview uses a numeric 1-10 scale for pain intensity. The Damages interview uses word-based scales (none/mild/moderate/severe/total). The Life Event interview uses a different 1-10 scale with its own descriptions. When an analyst tries to compare attack severity with damage severity, they are comparing apples and oranges. The fix: create one master severity scale used across ALL templates. A 7-point scale works well: 1=None, 2=Minimal, 3=Mild, 4=Moderate, 5=Significant, 6=Severe, 7=Extreme. Map all existing scales to this one.
- **Dates need precision indicators:** Some questions ask for exact dates (YYYY-MM-DD), but many TIs can only remember approximate timeframes. The Clues interview already handles this well with a 'date_confidence' field (exact/within_week/within_month/within_year). Every date field in every template should have this same confidence qualifier. Without it, the system cannot distinguish between 'this definitely happened on March 15, 2023' and 'this happened sometime in early 2023,' and treating both the same creates false precision in the analysis.
- **Locations need structured encoding:** Many location fields are free-text, meaning a TI might write 'my apartment in Brussels,' 'Brussels, Belgium,' 'Bruxelles,' or 'near Schuman metro.' These all refer to similar areas but a computer sees them as completely different strings of text. The fix: add structured fields for country (using ISO country codes like BE for Belgium), region/state, city, and optionally GPS coordinates alongside every location question. The free text stays for detail, but the structured fields enable geographic analysis.

> **WHAT IS 'DATA NORMALIZATION'?**
>
> Data normalization is the process of organizing data so that the same kind of information is always recorded in the same way. It is like deciding that everyone in a company will record dates as DD/MM/YYYY instead of some people using MM/DD/YYYY and others writing 'March fifteenth.' Without normalization, a computer cannot compare, sort, or aggregate data reliably. In the TI One Voice context, normalization means that when TI-A in Brussels and TI-B in Tokyo both report a 'severe' attack, the word 'severe' means the same thing and is recorded in the same format.

1.3.3 Make the Data More Machine-Readable

For the long-term goal of AI-driven analysis, every piece of information should be as easy as possible for a computer to process. This does not mean removing the human elements; it means adding structured markers alongside them.

- **Unique identifiers for everything:** Every incident, symptom, person, location, and piece of evidence mentioned anywhere in the platform should receive a unique ID number. Think of it like a filing system: instead of referring to 'that attack last Tuesday,' the system assigns it ID TI042-ATK-20260203-01 (meaning: TI number 42,

attack type, February 3 2026, first event that day). When the same TI later mentions this attack in their Damages interview ('the attack on February 3 caused me to miss work'), they can link to it by ID. Without IDs, connecting related information across interviews requires a human to read everything and manually make the connections. With IDs, a computer can do it instantly across millions of records.

- **Cross-reference fields:** When a Life Event is caused by an attack, or when a piece of damage results from a specific incident, there should be an explicit field to link them. Currently, these connections exist only in the narrative text, which means extracting them requires reading and interpreting natural language, something that is possible with AI but much less reliable than a direct link.
- **Timestamps with time zones:** Every submission should record not just the date but the exact time and the time zone. If a TI in Brussels and a TI in New York both report attacks at '3 AM,' that could be the same moment or six hours apart. Without timezone information, temporal correlation analysis is unreliable.
- **Confidence qualifiers:** For every observation or claim, add a field where the TI rates their confidence: 'I am certain,' 'I am fairly sure,' 'I am uncertain but this is my best recollection.' This allows analysis to weight high-confidence data more heavily and is critical for legal credibility.

▶ How Unique IDs Enable Pattern Detection

Imagine TI-A in Brussels reports an attack (ID: A-ATK-001) on March 5 at 02:15 AM involving V2K with a male voice speaking French. TI-B in Antwerp reports an attack (ID: B-ATK-047) on March 5 at 02:20 AM involving V2K with a male voice speaking French. TI-C in Liege reports an attack (ID: C-ATK-012) on March 5 at 02:30 AM involving V2K with a male voice speaking French. With unique IDs and timestamps, a simple database query can instantly find: 'Three TIs in Belgium reported V2K attacks within a 15-minute window on the same night, all describing a French-speaking male voice.' Without IDs and precise timestamps, this pattern would be invisible in a sea of narratives.

1.3.4 Specific Improvements to the Attack Interview

The Attack interview is currently designed as though a TI fills it out once. In practice, it should be used repeatedly, every time a significant attack occurs. To support this:

- Add an attack_session_id so each attack report is uniquely identifiable
- Add a link to the previous attack so escalation/de-escalation patterns can be tracked automatically
- Add a field for what the TI was doing when the attack happened (sleeping, working, commuting, eating, socializing, etc.) because correlations between activities and attacks might reveal targeting logic or operational patterns
- Replace the free-text body location with a standardized body zone map (head-front, head-back, chest, abdomen, left-arm, right-leg, etc.) so that body targeting can be statistically analyzed across the entire population. If 78% of TIs report pain concentrated in the head and chest, that tells us something about the technology being used.

- Add weather and environmental conditions at the time of the attack (temperature, humidity, indoor/outdoor) because some directed energy technologies have known interactions with atmospheric conditions

1.3.5 Specific Improvements to the Clues Interview

The Clues interview is the most analytically valuable template in the entire system. It is already very strong. Here are enhancements that would make it even more powerful:

- **Information leakage testing ('canary traps'):** Encourage TIs to conduct a simple experiment: share a unique piece of false information in one specific channel (for example, tell a specific person a made-up story, or write something distinctive in an email) and then monitor whether that information appears in V2K content or stalker behavior. If a TI tells their therapist they are planning to visit Rome, and the next day the V2K voices mention Rome, that is evidence of surveillance of the therapy session. This is called a 'canary trap' in intelligence work and it can provide very strong evidence of specific surveillance channels.

WHAT IS A CANARY TRAP?

A canary trap (also called a 'barium meal test') is a technique for detecting leaks. The person seeds different unique pieces of information to different suspected sources. When the information leaks, the unique detail reveals which source was compromised. The name comes from the historical practice of using canaries in coal mines to detect dangerous gases. In the TI context, this means deliberately creating unique, traceable information and monitoring whether it surfaces in targeting activity. For example, a TI could tell Friend A they are planning to move to City X, tell Friend B they are planning to move to City Y, and tell Friend C they are planning to move to City Z. If the targeting activity subsequently references City Y, it suggests Friend B (or their communications) are compromised.

- **Social network mapping:** Beyond listing individual conflicts, ask TIs to describe connections BETWEEN the people they name. Does your former boss know your new neighbor? Is the suspicious person at the gym also connected to someone at your workplace? These connections are what make the graph database powerful. Every connection a TI identifies becomes an edge in the network that can be computationally analyzed.
- **Specific technical fields for digital surveillance:** Instead of just asking 'have you experienced digital surveillance?', add fields for specific technical indicators: unusual IP addresses in device logs, unknown Bluetooth devices appearing, strange certificate warnings in browsers, unexpected DNS queries (when your device connects to unknown servers). Many TIs have technical skills and can provide this level of detail, which is directly analyzable and potentially traceable.
- **Timeline ordering exercise:** Ask TIs to put their key events in chronological order as a specific exercise. This helps them organize their own memories (which aids recall) and creates cleaner temporal data for analysis.

Part II: How to Store the Data for Maximum Analytical Power

This section describes the technical architecture for storing and organizing the data. Technical concepts are explained in plain language. The key idea is that you need not one, but three different ways of storing the same data, each optimized for different kinds of analysis.

2.1 The Three Storage Layers Explained

Think of the three layers like three different ways of organizing the same library. The first is a traditional card catalog (organized, searchable, but linear). The second is a wall-sized map showing how every book is connected to every other book (who influenced whom, which books cite which). The third is a system that understands the meaning of what is written in the books (can find books with similar ideas even if they use different words).

2.1.1 Layer 1: The Relational Database (The Card Catalog)

WHAT IS A RELATIONAL DATABASE?

A relational database stores information in tables (like spreadsheets) with rows and columns. Each table holds one type of information: one table for users, one for attacks, one for damages, etc. Tables are connected through shared IDs — for example, an attack record includes the user_id of the TI who reported it, linking the attack table to the users table. This is the most common type of database and is used by virtually every website and application you interact with. PostgreSQL, the specific relational database recommended here, is free, open-source, extremely reliable, and used by organizations from small startups to large banks and government agencies.

The relational database is where all the raw data lives. When a TI fills out an interview, each response goes into the appropriate table. This database handles the day-to-day operations of the platform: user accounts, interview submissions, searching and retrieving records.

Key design principles for this layer:

- **Never delete, only append:** When a TI updates an answer, the old answer is kept and a new version is added with a higher version number. This creates a complete historical record and is essential for legal admissibility. Courts need to see that evidence was not tampered with, and an append-only database proves this.
- **Hash every submission:** When a TI submits an interview, the system creates a 'digital fingerprint' (called a cryptographic hash) of the entire submission. This fingerprint is stored separately. If anyone later tries to alter the submission, the fingerprint will no longer match, proving the alteration. This is like a tamper-evident seal on a bottle.

WHAT IS A CRYPTOGRAPHIC HASH?

A cryptographic hash is a mathematical function that takes any piece of data (a document, a database record, even an entire hard drive) and produces a fixed-size string of characters that is unique to that specific data. Even changing a single letter in the original data produces a completely different hash. SHA-256, the standard used by Bitcoin and most security applications, produces a 64-character hexadecimal string. For example, hashing 'I was attacked on March 5'

might produce '3a7f2b9c...' (64 characters). If someone later changed 'March 5' to 'March 6', the hash would be completely different, instantly revealing the modification. It is computationally infeasible to create two different documents with the same hash. This makes hashes the gold standard for proving data integrity.

- **Timestamp with a trusted authority:** The system should use a Trusted Timestamp Authority (TSA) service, which is like getting a notarized stamp on each submission. The TSA cryptographically certifies that the data existed at a specific time. This prevents anyone from claiming the data was fabricated after the fact. This is the digital equivalent of mailing yourself a sealed envelope (the 'poor man's copyright') but much more legally robust.

2.1.2 Layer 2: The Graph Database (The Connection Map)

WHAT IS A GRAPH DATABASE?

A graph database stores information as a network of 'nodes' (things) and 'edges' (connections between things). A node might be a person, an organization, a location, an incident, or a piece of technology. An edge describes how two nodes are related: 'Person A WORKS_FOR Organization B,' 'Incident C OCCURRED_AT Location D,' 'TI-1 REPORTS_SIMILAR_SYMPTOMS_TO TI-2.' Unlike a traditional spreadsheet-style database where relationships are indirect (you have to look up IDs across tables), a graph database treats relationships as first-class data. This makes it extremely fast at answering questions like: 'Show me all the people connected to Organization X within two degrees of separation,' or 'Find all TIs who live within 50km of each other AND report attacks at similar times of day.' These are the kinds of queries that reveal hidden patterns.

This is where your ontology comes to life. The ontology you created defines 13 types of nodes (Person, Organization, Incident, Symptom, Technology, Evidence, Location, Temporal, Legal, Resource, Tactic, Program, Document) and dozens of relationship types connecting them. When the system is built, every piece of data from every interview becomes a node or an edge in this massive interconnected network.

How Graph Analysis Reveals Hidden Connections

Consider this scenario: TI-A in Brussels reports that their targeting began after a conflict with their employer, Company X. TI-B in Amsterdam reports organized stalking by individuals who seem professionally trained. TI-C in Paris reports digital surveillance of their devices. These three cases seem unrelated. But in the graph database, Company X is linked to a subsidiary, CompanySub-Y. CompanySub-Y is linked to SecurityFirm-Z (through a contract). SecurityFirm-Z employs individuals matching the descriptions provided by TI-B. SecurityFirm-Z also provides 'digital security services,' which could include the surveillance reported by TI-C. A graph query asking 'show me all paths connecting TI-A, TI-B, and TI-C through shared organizations' would reveal this chain. A human reading three separate case files might never make this connection. The graph database finds it in milliseconds.

Your ontology is comprehensive and well-structured. Here are the additions I recommend:

1. **Pattern nodes:** When the system detects a pattern (e.g., 'TIs in Belgian cities report V2K escalation after filing police complaints'), this pattern itself should become a node in the graph, linked to all the TIs and incidents that constitute it. This allows you

to query 'what patterns has this TI contributed to?' and 'what new data supports or contradicts this pattern?'

2. **AnalysisResult nodes:** Every time a computerized analysis is run, its results should be stored as a node in the graph. This creates an audit trail showing exactly how conclusions were derived from data. If evidence is ever presented in court, the opposing side will ask 'how did you reach this conclusion?' and the graph can show the complete chain from raw data through analytical steps to the finding.
3. **CONTRADICTS relationships:** Currently the ontology can link corroborating evidence but has no explicit way to record contradictions. Documenting contradictions is actually MORE important for credibility than documenting corroboration, because it shows the analysis is honest and does not cherry-pick supporting data while ignoring conflicting data.

2.1.3 Layer 3: The Vector Database (The Meaning Finder)

WHAT IS A VECTOR DATABASE AND WHY IS IT NEEDED?

This is perhaps the most important technical concept to understand, so let us take it slowly. When a TI writes a narrative about their experience, they use their own words. TI-A might write: 'I feel a burning sensation in my head, like someone is pressing a hot iron against my skull.' TI-B might write: 'There is an intense heat concentrated at the top of my head, as if focused sunlight is being directed at me.' TI-C might write: 'Cranial thermal attack, feels like microwave heating of brain tissue.' All three are describing essentially the same experience, but a traditional keyword search for 'burning' would only find TI-A's description. A vector database solves this by converting each piece of text into a mathematical representation (called a 'vector' or 'embedding') that captures its meaning rather than its exact words. Texts with similar meanings end up with similar mathematical representations, even if they share no words in common. This allows the system to answer the query: 'Find all descriptions similar in meaning to TI-A's account,' and it would return all three.

In technical terms, a vector embedding is a list of numbers (typically 384 to 1536 numbers long) that represents where a piece of text sits in 'meaning space.' Two texts that mean similar things will have similar numbers. The 'similarity' between two vectors is measured mathematically (using cosine similarity, which is essentially asking 'how much do these two arrows point in the same direction?').

The vector database is built by taking every free-text narrative response from every interview and converting it to a vector using an AI language model. These vectors are then stored in a searchable database. When you want to find similar experiences across the entire TI population, you convert the query into a vector and search for the closest matches.

▶ How Vector Similarity Finds Hidden Clusters

Suppose 47 TIs across 12 countries have independently described a very specific experience: a sensation that feels like their thoughts are being 'read' or 'extracted,' accompanied by a specific high-pitched tone in the left ear, occurring predominantly between 2-4 AM. They all describe it differently, using different languages, different metaphors, different levels of detail. A keyword search would never connect them all. But in vector space, their descriptions cluster together because the underlying meaning is similar. The AI identifies this cluster automatically, and the system flags: 'Cluster #23: 47 TIs reporting thought-extraction sensation with left-ear tinnitus, nocturnal, across 12 countries. Statistical probability of this cluster occurring by chance: 0.0003%.' That is a pattern worth investigating.

2.2 How the Three Layers Work Together

The three databases are not separate systems; they are three views of the same underlying data, each optimized for different questions:

Question Type	Which Database Answers It	Example Question
Simple lookup	Relational (PostgreSQL): Find specific records	'Show me all attack reports from TI-42 in January 2026'
Statistical aggregation	Relational (PostgreSQL): Count, average, group data	'What percentage of TIs in Europe report V2K?'
Relationship discovery	Graph (Kuzu/Neo4j): Traverse connections	'Which organizations appear in the networks of TIs who share similar onset dates?'
Community detection	Graph (Kuzu/Neo4j): Find clusters	'Are there groups of TIs connected through shared persons of interest who don't know each other?'
Semantic similarity	Vector (pgvector/Qdrant): Meaning-based search	'Find all TIs whose attack descriptions are similar in meaning to this one'
Anomaly detection	All three combined	'Which TI reports deviate most from the typical pattern? (possible disinformation or unique case)'

2.3 The Data Pipeline: How Data Flows Through the System

WHAT IS A DATA PIPELINE?

A data pipeline is a series of automated steps that data goes through from the moment it is collected to the moment it is ready for analysis. Think of it like a factory assembly line: raw materials come in at one end, go through various processing stations, and finished products come out the other end. In this case, the raw material is a TI's interview submission, and the finished product is a set of analyzed, indexed, searchable, interconnected data points ready for pattern detection. The pipeline runs automatically, typically on a schedule (nightly, weekly), without human intervention.

Here is what happens when a TI submits an interview, step by step:

1. **Step 1 — Intake and validation:** The TI fills out the interview on the platform. The system checks that required fields are completed, dates are in the right format, and selections are from the allowed options. The submission is stored in the relational database with a timestamp and a cryptographic hash. The TI receives confirmation.
2. **Step 2 — Entity extraction:** An automated process reads through the submission and identifies entities: names of people, organizations, locations, dates, and other specific data points. Structured fields are extracted directly. Free-text narratives are processed using Natural Language Processing (NLP) to extract additional entities. For example, if a TI writes 'My former boss John at TechCorp moved to the same neighborhood in June 2024,' the system extracts: Person(John, former boss),

Organization(TechCorp), Location(same neighborhood), Date(June 2024), Relationship(John EMPLOYED_BY TechCorp).

WHAT IS NATURAL LANGUAGE PROCESSING (NLP)?

NLP is a branch of artificial intelligence that deals with the interaction between computers and human language. It allows computers to read, understand (to some degree), and extract information from text. Simple NLP can identify names of people, places, and organizations in text (called 'Named Entity Recognition'). Advanced NLP can understand the sentiment of text (positive/negative), summarize long documents, translate between languages, and even answer questions about text. In the TI One Voice context, NLP is used to automatically extract structured data points from the free-text narrative responses that TIs write in their own words.

3. **Step 3 — Graph construction:** The extracted entities become nodes in the graph database, and the relationships between them become edges. If this TI was already in the graph, their existing nodes are updated. New connections to other TIs' data are created where they exist (e.g., if another TI also mentions TechCorp).
4. **Step 4 — Embedding generation:** The narrative text from the submission is converted into vector embeddings and stored in the vector database. This makes it immediately searchable by meaning.
5. **Step 5 — Pattern matching:** The system checks whether the new submission matches any existing patterns. If TI-42's new attack report matches a pattern that 23 other TIs have also contributed to, the pattern's confidence increases. If a new pattern is detected (a combination that has never been seen before but is now appearing for the third time), it is flagged for review.
6. **Step 6 — Anomaly detection:** The system checks whether anything about the new submission is unusual: an attack at an unprecedented time, a symptom that no other TI has reported, or conversely, a submission that is suspiciously similar to another TI's submission (which might indicate copied data). Anomalies are flagged for human review.

Part III: From Data to Evidence — The Analysis Framework

This is the heart of the blueprint: how to actually turn the collected data into evidence. The analysis happens in three phases, driven by how much data has been collected. Each phase uses increasingly sophisticated techniques.

3.1 Phase 1: Counting and Describing (Year 1, 50-500 TIs)

With a relatively small dataset, the focus is on basic statistics that paint a clear picture of the TI population and their experiences. Even simple counts can be powerful.

WHAT IS DESCRIPTIVE ANALYTICS?

Descriptive analytics answers the question 'what happened?' using basic statistics: counts, averages, percentages, and distributions. It is the foundation of all analysis. Before you can detect patterns, you need to know the baseline: what does the average TI experience look like? What are the most common symptoms? What is the typical timeline? Descriptive analytics creates this baseline. Think of it as taking a census of the TI community.

Key analyses in this phase:

- **Demographic profile:** What is the age distribution of TIs at the time targeting began? What is the geographic distribution? What professions are represented? What is the gender split? Compare these against general population statistics. If, for example, TIs are 5x more likely to have worked in government or military than the general population, that is a significant finding even with a small sample.

Why Demographic Comparison Matters

Suppose analysis reveals that 23% of registered TIs previously worked for defense contractors, compared to approximately 1% of the general population. This 23x overrepresentation is strong statistical evidence that there is a connection between defense industry employment and targeting. It does not prove causation (it does not tell you why), but it narrows the field of investigation dramatically. Similarly, if 40% of TIs report that targeting began within 6 months of a workplace dispute, that correlation is worth investigating.

- **Symptom prevalence and co-occurrence:** What percentage of TIs report each type of symptom? More importantly, which symptoms appear together? Create a 'co-occurrence matrix' showing how often each pair of symptoms appears in the same TI. If V2K and specific sleep disruption patterns always appear together but DEW and organized stalking are independent, this might indicate different technologies or different perpetrator groups.
- **Geographic heat mapping:** Plot every TI's location on a map and look for clusters. Are there disproportionately many TIs in certain cities? Near certain facilities? In certain countries? Geographic clustering is one of the strongest indicators of a coordinated rather than random phenomenon.
- **Aggregate damage quantification:** Calculate the total financial damages across the entire TI population: total income lost, total medical costs, total legal costs, total relocation costs. Even rough estimates are powerful for advocacy: 'Our 500 members

have collectively suffered an estimated €47 million in documented financial damages' is a number that gets attention.

📁 REAL-WORLD CASE: How Basic Statistics Changed Policy: The Workplace Harassment Parallel

In the early days of the #MeToo movement, individual stories were impactful but easily dismissed as isolated incidents. What changed the conversation was data: the Equal Employment Opportunity Commission reported that 75% of workplace harassment goes unreported, that the average settlement cost employers $125,000, and that certain industries had harassment rates 3-5x higher than others. These basic descriptive statistics transformed the narrative from 'individual bad actors' to 'systemic problem requiring structural solutions.' The TI One Voice platform aims to produce the same kind of transformation: from 'isolated individuals with unusual beliefs' to 'a population of thousands with statistically coherent, internally consistent, and geographically patterned experiences.'

3.2 Phase 2: Finding Correlations and Connections (Year 2-3, 500-5,000 TIs)

With a larger dataset, the analysis shifts from describing what exists to discovering connections that were not previously visible.

3.2.1 Cross-Case Entity Resolution

WHAT IS ENTITY RESOLUTION?

Entity resolution is the process of determining whether two pieces of data refer to the same real-world entity, even when they are described differently. For example, TI-A might mention 'a tall man with a scar who drives a black SUV,' and TI-B might mention 'a scarred individual, approximately 190cm, seen in a dark-colored vehicle.' Entity resolution uses algorithms to determine that these might be describing the same person. This is one of the most valuable analytical techniques because it reveals connections between cases that the TIs themselves may not be aware of. It is used extensively in law enforcement ('does this suspect match any known offenders?'), intelligence analysis, and fraud detection.

In the TI One Voice context, entity resolution would be applied to identify when different TIs are unknowingly referring to the same person, organization, location, or event. This is done through a combination of:

- Exact matching: same names, same addresses, same organization names
- Fuzzy matching: similar but not identical descriptions (allowing for misspellings, nicknames, partial names)
- Attribute matching: matching on combinations of characteristics (age + appearance + vehicle + location) even when no single attribute is an exact match
- Temporal matching: events that occur at the same time in the same area

3.2.2 Temporal Sequence Mining

WHAT IS SEQUENCE MINING?

Sequence mining is a technique for finding patterns in ordered sequences of events. Instead of asking 'what events are common?' it asks 'what sequences of events are common?' For example: 'TI files a complaint → TI experiences intensified attacks within 7 days → TI's employer receives anonymous negative reports about them → TI loses their job within 30 days.' If this exact sequence appears in 40% of all TI cases, that is extremely significant. It suggests a playbook — a standard procedure being followed by the perpetrators. Sequence mining algorithms (like GSP and PrefixSpan) automatically discover these repeated sequences in the data without being told what to look for.

▶ Sequence Mining in Practice

The combined timeline of 2,000 TIs reveals the following sequence appearing in 34% of cases: (1) TI begins documenting or reporting their experiences publicly, (2) Within 1-4 weeks, new organized stalking behavior begins, (3) Within 2-8 weeks, TI's close relationships start deteriorating (family members report being 'approached' or 'warned'), (4) Within 3-6 months, TI experiences job loss or career disruption. This pattern, discovered automatically by the algorithm, suggests a coordinated escalation protocol. No single TI would recognize this pattern in their own life because they experience it once. The algorithm sees it repeated across hundreds of cases.

3.2.3 Geographic-Temporal Clustering

This technique plots attacks on a map AND a timeline simultaneously, looking for events that cluster both in space and in time. The algorithm used (DBSCAN or HDBSCAN) automatically groups events that are close to each other in both geography and time, without being told how many clusters to look for or where they should be.

WHAT IS DBSCAN?

DBSCAN stands for Density-Based Spatial Clustering of Applications with Noise. In plain language, it is an algorithm that finds 'crowds' in data. Imagine scattering dots on a map: some dots form tight groups, others are isolated. DBSCAN automatically identifies the tight groups (clusters) and labels the isolated dots as 'noise.' What makes it particularly useful for TI data is that it does not require you to specify how many clusters exist in advance (unlike some other algorithms), and it can find clusters of any shape (not just circular ones). Applied to TI data with three dimensions (latitude, longitude, time), it can find waves of targeting sweeping across a region.

▶ Geographic-Temporal Clustering Reveals a Wave

Analysis of 3,000 attack reports over 12 months reveals a cluster: 47 TIs in a 200km radius of a specific location all reported intensified attacks during the same two-week period in October 2025. Before and after that period, their attack levels were at their individual baselines. 35 of these TIs had no known contact with each other. The geographic center of the cluster is 15km from a known military research facility. This does not prove anything about the facility. But it is a specific, documented, statistically significant anomaly that a formal investigation could use as a starting point.

3.3 Phase 3: AI-Driven Evidence Construction (Year 3-5, 5,000+ TIs)

With a large, mature dataset, the most powerful analytical techniques become available:

3.3.1 Topic Modeling: What Are People Really Talking About?

WHAT IS TOPIC MODELING?

Topic modeling is an AI technique that reads a large collection of text documents and automatically discovers the main 'topics' or themes that run through them. It does this without being told what to look for. A topic modeling algorithm like BERTopic might read 50,000 narrative responses from TIs and discover 47 distinct topics, such as 'nocturnal attacks with thermal sensation,' 'post-complaint retaliation,' 'family relationship deterioration,' 'electronic device interference patterns,' etc. Some topics might be expected. Others might be surprises — themes that appear frequently but that nobody had specifically thought to ask about. These surprise topics often represent the most valuable discoveries.

3.3.2 Graph Neural Networks: Predicting Missing Links

WHAT ARE GRAPH NEURAL NETWORKS (GNNs)?

Graph Neural Networks are a type of AI that learns from the structure of a network (a graph). Instead of analyzing rows in a spreadsheet, GNNs analyze the connections between nodes. They can be trained to predict: (1) 'What links are likely missing from this graph?' (if Organization A is connected to Organization B, and Organization B is connected to suspicious Organization C, the GNN might predict that Organization A is also connected to Organization C, even though no TI has reported this link), (2) 'Which nodes are most central to the network?' (identifying the organizations or individuals that appear most frequently and most centrally across all TI cases), and (3) 'Are there sub-communities within the graph?' (groups of TIs and entities that are more connected to each other than to the rest of the network, possibly indicating distinct targeting programs or perpetrator groups).

3.3.3 Causal Inference: Does A Actually Cause B?

With enough longitudinal data (years of repeated measurements from thousands of TIs), it becomes possible to move beyond correlation ('these things happen together') to causation ('this thing causes that thing').

WHAT IS CAUSAL INFERENCE?

Causal inference is a set of statistical techniques for determining whether a relationship between two variables is causal (A causes B) rather than merely correlational (A and B happen together, but maybe both are caused by C). For example, the observation that 'TIs who file police reports experience increased attacks' is a correlation. It could mean: (a) filing a report triggers retaliation (causal), (b) TIs who are more heavily attacked are more likely to file reports (reverse causation), or (c) some third factor (like geographic location) independently causes both more attacks and more likelihood of filing reports (confounding). Techniques like Granger causality testing, instrumental variables, and difference-in-differences analysis can help distinguish between these explanations. They require large amounts of longitudinal data, which is why this is a Phase 3 activity.

Causal Inference in Action

With 5 years of data from 5,000 TIs, the system applies Granger causality testing. Result: 'Filing a formal complaint with national-level law enforcement Granger-causes a statistically significant increase in attack intensity within 14 days ($p < 0.001$), after controlling for baseline attack levels, geographic location, and seasonal variation. This effect is not observed when complaints are filed with local police or human rights organizations.' This finding, if robust, constitutes statistical evidence of retaliation — and the specificity (national-level law enforcement but not local police) narrows the potential perpetrator pool significantly.

3.4 Building an Evidence Package

Raw data is not evidence. Evidence is data that has been processed, validated, contextualized, and presented in a way that supports specific claims. Here is how the system turns data into evidence:

1. **Corroboration requirement:** No finding is promoted to 'evidence' based on a single TI's data. The minimum threshold for a 'corroborated finding' should be 3 or more independent TIs with no known contact before their reports. Independent corroboration is the gold standard in both journalism and law.
2. **Control comparisons:** For every pattern detected, the system should check whether the pattern also appears in a control group. If TI locations cluster around military bases, also check whether they cluster around hospitals, universities, or supermarkets. If they cluster only around military bases and not other facility types, the finding is much stronger.
3. **Null hypothesis testing:** For every statistical finding, calculate the probability that the result could have occurred by chance. In science, a result is considered 'statistically significant' if this probability is less than 5% ($p < 0.05$). For evidence intended for legal proceedings, an even stricter threshold ($p < 0.01$ or 1% chance) should be used.

WHAT IS A P-VALUE?

A p-value is the probability of seeing a result as extreme as the one you observed, assuming that nothing interesting is actually happening (the 'null hypothesis'). For example, if you find that 73% of TIs lost their job within 2 years of targeting onset, the p-value tells you: 'If targeting had NO effect on employment, what is the probability of observing 73% job loss just by chance in a group this size?' If the p-value is 0.001, that means there is only a 0.1% chance this happened by coincidence. The smaller the p-value, the stronger the evidence that the pattern is real and not random.

4. **Falsifiability documentation:** For every conclusion, document what would disprove it. This is what separates science from confirmation bias. If the analysis finds geographic clustering, document the specific control tests that were run and their results. Courts respect methodology that actively tries to disprove its own findings.

5. **Reproducibility:** Every analytical procedure must be documented in sufficient detail that an independent expert could repeat the analysis and get the same results. This means documenting the exact algorithms used, the parameters chosen, the data included and excluded, and the software versions. This is essential for the Daubert standard, which many courts use to determine whether scientific evidence is admissible.

WHAT IS THE DAUBERT STANDARD?

In many legal systems (particularly in the US, but increasingly influential elsewhere), the Daubert standard determines whether expert testimony and scientific evidence can be presented in court. The criteria include: (1) the methodology can be and has been tested, (2) it has been subjected to peer review, (3) it has a known error rate, (4) there are standards controlling its operation, and (5) it is generally accepted in the relevant scientific community. The TI One Voice data analysis system should be designed from the start to meet these criteria. This means using published, peer-reviewed algorithms; documenting error rates; maintaining version control; and submitting methodology for external review.

Part IV: Protecting the Data and the People Behind It

The TI One Voice platform collects some of the most sensitive personal information imaginable: descriptions of abuse, health conditions, psychological states, financial details, identities of suspected perpetrators, and more. Protecting this data is not just an ethical obligation; it is a practical necessity, because if the data is compromised, it could be used to further harm TIs, and if data security is weak, the entire dataset's credibility as evidence is undermined.

4.1 Security: Keeping the Data Safe

- **Encryption at rest:** All data stored on the server's hard drives is encrypted. This means even if someone physically steals the server's hard drive, they cannot read the data without the encryption key. The standard is AES-256, the same encryption standard used by banks and governments. 'At rest' means the data is encrypted when it is sitting on disk, as opposed to 'in transit' (when it is being sent over the internet).
- **Encryption in transit:** All data sent between a TI's device and the server is encrypted using TLS 1.3 (the latest version of the protocol that makes the 'https' in web addresses secure). This prevents anyone who might be intercepting the TI's internet traffic from reading the data being submitted.
- **Pseudonymization:** Each TI is assigned a random pseudonymous ID (like TI-7X9K2). Their real name and the pseudonymous ID are stored in different systems with separate access controls. All analysis is conducted on pseudonymized data. This means even a data analyst working on pattern detection never sees real names or personally identifiable information.
- **Audit logging:** Every time anyone accesses, queries, modifies, or exports any data, the system records who did it, when, and what they accessed. These logs are immutable (cannot be edited or deleted). This creates a tamper-evident record of all data access, which is essential for chain of custody and for detecting unauthorized access.

4.2 GDPR Compliance

WHAT IS GDPR?

The General Data Protection Regulation (GDPR) is a European Union law that governs how personal data is collected, stored, and used. Since the platform is based in Brussels, GDPR applies fully. Key requirements include: you must have a lawful basis for processing data (consent is the most common), you must tell people exactly what you will do with their data, people have the right to see all data you hold about them, people have the right to have their data deleted ('right to be forgotten'), and data breaches must be reported within 72 hours. Non-compliance can result in fines of up to €20 million or 4% of annual turnover. For the TI One Voice platform, the lawful basis for processing is a combination of explicit consent and legitimate interest in pursuing legal proceedings.

Key GDPR implementations for the platform:

- Granular consent: TIs choose exactly what their data can be used for. They might consent to personal documentation but not aggregate analysis, or consent to analysis but not sharing with external legal teams.
- Right to access: TIs can download all their data at any time in a standard format.
- Right to erasure: TIs can request deletion of all their data, which cascades across all three database layers.
- Data Protection Impact Assessment (DPIA): Conduct a formal DPIA before launching, documenting the risks of processing this sensitive data and the safeguards in place.

Part V: How TIs Should Use the Platform for Maximum Impact

The best data architecture in the world is useless if TIs do not contribute high-quality data regularly. This section provides specific guidance on how TIs should interact with the platform to maximize both their personal documentation and the collective analytical power.

5.1 The Onboarding Journey (First Week)

The first week on the platform is the most important. This is when a TI creates the foundation of their case file. Here is the recommended sequence:

1. **Day 1 — Sign the Declaration and complete your profile:** This takes about 30 minutes. Set up your account, configure your security settings, and sign the TI One Voice Declaration.
2. **Day 1-3 — Complete the TI Start (Onset) interview:** This is the most important single contribution you will make to the platform. Set aside 2-3 uninterrupted hours. Have your personal records available: old calendars, emails, medical records, employment records. The more precisely you can date events and describe circumstances, the more valuable your data is for analysis. Do not rush this.
3. **Day 3-5 — Complete the Clues interview:** This captures your current best recollection of investigative leads. Again, take your time. Review your notes, photos, screenshots, and any documentation you have collected. This can and should be updated later, but your initial submission captures details that might fade from memory.
4. **Day 5-7 — Complete the Damages interview:** This establishes your baseline damage assessment. Try to be as specific as possible about financial amounts, even if estimates. 'Approximately €15,000 in lost income' is much more useful than 'significant income loss.'

5.2 Regular Documentation Habits

After onboarding, the goal is to make platform documentation a regular habit, like keeping a journal. Here is the recommended schedule:

Activity	When	Time Needed	Tips for High-Quality Submissions
Attack report	Within 24 hours of each significant attack	15-30 min	Write while the experience is fresh. Include exact times, what you were doing, body locations, and intensity. A report written the same day is 10x more valuable than one written a week later.
Life Event log	Within 48 hours of any significant event	20-45 min	Document both positive and negative events. A period of reduced attacks is as important to document as an escalation. Note whether you think the event is connected to targeting.

Activity	When	Time Needed	Tips for High-Quality Submissions
Clues update	Monthly (or when you discover something new)	30-60 min	Review your month. Did you notice anything new? New suspicious people? New electronic anomalies? Try the canary trap experiment (share unique false info and see if it surfaces).
Damages update	Every 3 months	45-60 min	Compare to your previous assessment. Has your situation improved or worsened? Track financial costs with receipts if possible. Document relationship changes.
Environmental baseline	Monthly (or after any move)	30-45 min	Take RF/EMF readings at the same locations in your home at the same time of day. Log visible WiFi networks and Bluetooth devices. Note any physical changes near your residence.

5.3 The Golden Rules of Data Quality

These rules, if followed by every TI, will dramatically increase the analytical power of the collective dataset:

1. **Document immediately, reflect later:** The single biggest factor in data quality is freshness. Write your attack report the same day. Log the life event the same day. Memory fades fast, and the details that enable pattern detection (exact times, specific sensations, precise locations) are the first to go. You can always add reflections and interpretations later, but the raw observation must be captured while fresh.
2. **Separate what you SAW from what you THINK:** There is a crucial difference between 'I felt a burning sensation in my left shoulder at 3:15 AM' (an observation) and 'I believe a directed energy weapon was aimed at my left shoulder' (an interpretation). Both are valuable, but they serve different analytical purposes. The platform should ideally have separate fields for each, and TIs should consciously distinguish between them. Observations are objective data. Interpretations are hypotheses.
3. **Be specific, not general:** Instead of 'attacks are getting worse,' write 'attacks increased from approximately 2 per week in January to approximately 5 per week in February, with intensity increasing from an average of 4/10 to an average of 7/10.' Specific numbers, even if estimated, are infinitely more analyzable than qualitative descriptions.
4. **Document the ABSENCE of events:** A week without attacks is as important as a week with attacks. The conditions under which attacks do NOT occur are often more analytically valuable than the attacks themselves, because they might reveal what stops the attacks. Did the attacks stop when you traveled to a specific country? When you stayed at a friend's house? When the power went out in your neighborhood? Document these absences and the circumstances.

5. **Cross-reference everything:** When you submit a new attack report, link it to previous related entries. 'This attack is similar to Attack #12 but more intense.' 'This life event (job loss) is connected to the damage reported in my Q3 Damages assessment.' Every link you create is an edge in the graph database that strengthens the analytical power of the system.
6. **Do not self-censor:** Include weak leads, uncertain observations, and half-formed theories. Pattern detection works by finding correlations that individual humans cannot see. Something that seems trivial or uncertain to you might turn out to be the missing piece that connects multiple TI cases. The system can handle noise; what it cannot handle is missing data.

5.4 Keeping TIs Engaged Over Time

Long-term data quality depends on TIs continuing to contribute over months and years. The platform should help maintain engagement through:

- **Progress dashboards:** Show each TI their documentation completeness: 'You have completed 4 of 5 interview types. Your data has contributed to 3 detected patterns. Your documentation quality score is 82%.' This creates a sense of purpose and progress.
- **Community milestones:** Share collective achievements: '1,000 attack reports documented this month. 50 corroborated patterns identified. 3 new geographic clusters discovered.' This builds momentum and reinforces the message that every contribution matters.
- **Feedback loops:** When a TI's data contributes to a significant finding, let them know (without revealing other TIs' identities): 'Your attack report from March 5 matches a pattern seen in 23 other independent reports, strengthening a corroborated finding.' This tangible feedback motivates continued participation.
- **Gentle reminders:** If a TI has not submitted an attack report in 30 days or a damages assessment in 100 days, send a kind reminder framed around their benefit: 'Your regular documentation helps build your personal case file and strengthens the collective evidence. Have there been any events you would like to document?'

Part VI: The Step-by-Step Implementation Roadmap

6.1 Year 1: Lay the Foundation (2026)

The first year is about getting the fundamentals right. It is tempting to rush to AI analysis, but without a solid data foundation, advanced analysis will produce unreliable results. Think of it as building a house: the foundation is not exciting, but without it, everything built on top collapses.

1. Finalize all interview templates with the changes recommended in Part I. Create the 6th Environmental Baseline template. Publish version 2.0 of all templates.
2. Set up the PostgreSQL database with the normalized schema, audit logging, cryptographic hashing, and trusted timestamps. Get this right from day one because retrofitting security features later is extremely difficult.
3. Build the basic ETL (Extract-Transform-Load) pipeline that automatically populates the graph database whenever new interview data is submitted.
4. Implement the data governance framework: consent management, pseudonymization, role-based access control, GDPR compliance.
5. Deploy the platform and begin active TI onboarding. Target: 100-500 TIs completing full onboarding (all 5+ interviews).
6. Produce the first descriptive analytics report with basic statistics, geographic distribution, and symptom prevalence.

6.2 Year 2-3: Scale and Discover (2027-2028)

1. Scale to 2,000-5,000 active TIs through community outreach, social media, and word of mouth.
2. Deploy the vector database and begin generating semantic embeddings of all narrative responses.
3. Implement cross-case entity resolution: automatically detect when different TIs mention the same people, organizations, or locations.
4. Build geographic and temporal heat maps and clustering analysis.
5. Begin automated pattern detection and establish a review committee to validate findings before they are promoted to evidence.
6. Produce the first comprehensive cross-case analysis reports.

6.3 Year 3-5: AI-Driven Evidence Construction (2028-2030)

1. Deploy advanced NLP: topic modeling, sentiment analysis, automated entity extraction from narratives.
2. Train graph neural networks for link prediction and community detection in the knowledge graph.
3. Apply causal inference analysis to the longitudinal life event data.
4. Build the automated evidence package generator.
5. Produce comprehensive 'State of Targeting' reports with full statistical rigor.
6. Engage legal counsel to assess which findings meet evidentiary standards in relevant jurisdictions (Belgium/EU, US, UK, etc.).
7. Pursue the most promising legal, regulatory, or investigative avenues based on constructed evidence.

Part VII: Risks and How to Handle Them

7.1 Data Poisoning by Disinformation Agents

The risk: People could create fake TI accounts and submit fabricated data designed to either discredit the platform's findings or to introduce false patterns that waste analytical resources.

The mitigation: Implement a tiered verification system. All TIs start as 'unverified.' After providing basic identity verification (which can be pseudonymous), they move to 'verified.' After consistent, coherent submissions over time, they move to 'established.' The analysis system weights data from established accounts more heavily than from new unverified accounts. Additionally, anomaly detection algorithms can flag submissions that are statistically unusual: either too perfectly matching an existing pattern (suggesting copying) or too different from all other submissions (suggesting fabrication). Neither is conclusive, but both are worth human review.

> **REAL-WORLD CASE: How Wikipedia Handles Disinformation**
>
> Wikipedia faces a similar challenge: anyone can edit articles, so how do you prevent deliberate misinformation? Wikipedia's approach includes: (1) tiered editor permissions (new accounts have restrictions), (2) automated bots that detect suspicious editing patterns, (3) requiring citations for claims, (4) community review of flagged content, and (5) version history that makes all changes transparent. The TI One Voice platform should implement analogous protections: tiered trust levels, automated anomaly detection, encouraging documentation/evidence alongside claims, human review of flagged data, and complete version histories.

7.2 Platform Security Compromise

The risk: Attackers gain access to the database and either steal sensitive TI data (which could be used for further targeting) or alter data (which could undermine evidence credibility).

The mitigation: Defense in depth. Encryption at rest means stolen data is unreadable. Pseudonymization means even decrypted data does not reveal real identities without a separate key stored elsewhere. The cryptographic hashes on every submission mean any alteration is immediately detectable. Regular security audits, penetration testing, and bug bounty programs help identify vulnerabilities before attackers do.

7.3 Confirmation Bias in Analysis

The risk: The analysts, who believe targeting is real, unconsciously look for patterns that confirm their belief while ignoring evidence that contradicts it. This is a legitimate scientific concern and one that critics will certainly raise.

The mitigation: Pre-register analysis plans (publicly declare what you are going to analyze and how before looking at the data). Run control comparisons for every finding. Actively seek disconfirming evidence. Include a 'devil's advocate' role in the review committee, someone whose job is to find alternative explanations. Document and publish null results (analyses that found nothing significant) alongside positive findings. This level of rigor is what distinguishes evidence from advocacy.

7.4 Low Engagement and Attrition

The risk: TIs sign up but stop contributing after a few weeks, resulting in incomplete longitudinal data that weakens the analytical power of the system.

The mitigation: Make documentation as frictionless as possible. Mobile-first design. Allow voice-to-text input. Implement the gamification features described in Part V. Build a supportive community around the platform so that it provides social value beyond data collection. Regularly communicate the impact of contributions. Consider implementing a buddy system where TIs can encourage each other to maintain documentation habits.

7.5 Legal Challenges to the Methodology

The risk: When the evidence is presented, opposing parties challenge the methodology used to produce it, potentially getting it excluded from legal proceedings.

The mitigation: Design for legal admissibility from day one. Use published, peer-reviewed algorithms. Document everything: data collection procedures, analytical methods, parameter choices, software versions, error rates. Submit the methodology for external peer review before presenting evidence. Engage expert witnesses (statisticians, data scientists, forensic analysts) who can testify to the soundness of the methodology. Meet the Daubert standard criteria proactively rather than defensively.

Conclusion: Every Data Point Matters

The TI One Voice platform is more than a website where people share their stories. It is an evidence construction engine. Every interview completed, every attack documented, every life event recorded, and every environmental measurement taken is a data point. Alone, it is a personal account. But aggregated across thousands of people, organized in the right databases, processed through the right analytical pipeline, and subjected to rigorous statistical testing, these data points become something much more powerful: evidence.

The criminals behind targeting operations rely on secrecy and on the isolation and discrediting of their individual victims. A platform that connects thousands of victims, structures their experiences into analyzable data, and applies computational pattern detection to the aggregate is the most direct counter-strategy possible.

History shows that secret programs leave traces, and that systematic data collection eventually exposes them. MKUltra was exposed through financial records. COINTELPRO was exposed through stolen documents. The Catholic Church abuse scandal was exposed through systematic victim testimony collection. Havana Syndrome was recognized through consistent, documented symptom patterns across independent cases. The Flint water crisis was proven through systematic measurement data.

The TI One Voice platform combines all of these approaches: victim testimony, systematic documentation, structured data collection, and environmental measurement. The techniques exist. The technology exists. What is needed is the data, and the data comes from TIs who commit to the discipline of thorough, regular, honest documentation.

What you need to do right now is straightforward: implement the data architecture correctly, refine the interview templates as recommended, and begin onboarding TIs. The analytical power will grow organically as the dataset grows. The algorithms will reveal patterns that no individual can see. The evidence will construct itself from the aggregate.

It may take years. But every journey starts with the first step, and every evidence package starts with the first data point.

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